ERK'94

Portorož, Slovenija, 26. – 28. september 1994

Zbornik
tretje Elektrotehniške in računalniške konference ERK'94
Proceedings of the Third
Electrotechnical and Computer Science Conference ERK'94

Zvezek B / Volume B

Računalništvo in informatika / Computer and Information Science
Umetna inteligenca / Artificial Intelligence
Robotika / Robotics
Razpoznavanje vzorcev / Pattern Recognition
Biomedicinska tehnika / Biomedical Engineering
Študentski članki / Student Papers

Uredila / Edited by
Baldomir Zajc, Franc Solina

Slovenska sekcija IEEE / Slovenia Section IEEE

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Slovenska sekcija IEEE

Ljubljana • Slovenija

CIP - Kataložni zapis o publikaciji
Narodna in univerzitetna knjižnica, Ljubljana

621.3(063)

ELEKTROTEHNIŠKA in računalniška konferenca (3 ; 1994 ; Portorož)
Zbornik tretje Elektrotehniške in računalniške konference ERK '94, 26. - 28. september 1994, Portorož, Slovenija. Zv. B / uredila Baldomir Zajc, Franc Solina. - Ljubljana : Slovenska sekcija IEEE, 1994

Besedilo slov. ali angl. - Na vzpor. nasl. str.: Proceedings of the Third Electrotechnical and Computer Science Conference ERK '94. - Vsebina na nasl. str.: Računalništvo in informatika ; Umetna inteligenca ; Robotika ; Razpoznavanje vzorcev ; Biomedicinska tehnika ; Studentski članki

ISBN 961-6062-04-2

1. Solina, Franc 2. Zajc, Baldomir. - I. Electrotechnical and Computer Science Conference (3 ; 1994 ; Portorož) glej Elektrotehniška in računalniška konferenca (3 ; 1994 ; Portorož). - II. ERK '94 glej Elektrotehniška in računalniška konferenca (3 ; 1994 ; Portorož)
42571008

Pri organizaciji Elektrotehniške in računalniške konference ERK'94
so sodelovala naslednja društva:

Elektrotehniška zveza Slovenije,
Društvo avtomatikov Slovenije,
Slovensko društvo za merilno-procesno tehniko (ISEMEC 94),
CIGRE,
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Slovensko društvo za umetno inteligenco,
Slovensko društvo za razpoznavanje vzorcev,
Slovensko društvo za simulacijo in modeliranje.

Organizacijo konference in izdajo zbornika je finančno podprlo Ministrstvo za znanost in tehnologijo Republike Slovenije

Sponzor: Hermes SoftLab, Ljubljana

Slovenska sekcija IEEE
Fakulteta za elektrotehniko in računalništvo
Tržaška 25, 61001 Ljubljana, Slovenija

Tisk: SOMARU d.o.o. Ljubljana

Construction of CAD Models for Reverse Engineering *

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Abstract

Construction of complete 3-D models suitable for CAD systems from a set of range images consists of a few typical steps: range image acquisition from different viewpoints, building range image representations, registering the range images or their representations, merging range images or representations, and optional next viewpoint planning, The paper addresses characteristic requirements of each of the steps and assesses the feasibility of superellipsoids as volumetric representation for range images in each step. The object domain is restricted to rigid objects that can be modelled as a composition of non-deformed superellipsoids in a simple constructive solid geometry manner using only union Boolean operations.

1 Introduction

Range image acquisition by 3-D imaging sensors inherently produces only partial 3-D description from a single viewpoint. This description represents a distance between an image plane and points on the object surface in such a way that for each point in the plane there is at most one corresponding point on the object surface. The distance of the points from the object surface to the image plane can be represented as a function $z(x,y)$. Because of this restriction such description is often referred to as 2.5-D data. Throughout this paper we will use the term *range image* to refer to this 2.5-D data and *3-D description* to refer to a set of 3-D points from the object surface. It is quite obvious that each range image is also a 3-D description but the reverse is generally not true.

Evidently, the main reason for partial description is self-occlusion. Besides, geometry of sensor setup might further reduce the space where 3-D data can be deduced (see [10] for an example of such sensor setup). In order to produce a complete 3-D description, that is a set of densely sampled 3-D points from the object surface, we have to merge the range images obtained from several viewpoints. The later implies either object manipulation or change of sensor position to achieve a relative change of position and orientation of the object with respect to the sensor.

The process of construction of a complete 3-D model consists of the following steps:

- range image acquisition from different viewpoints,
- building range image representations,
- registering of range images or their representations,
- merging range images or their representations,
- optional next viewpoint planning.

Range image representation critically affects the process of construction. Ideal representation should be computationally efficiently used in all steps of the process, that is it should be easily computed from the range image, support local shape matching, surface point visibility test, finding rigid transformation between two range views, and merging of range images. It would also serve as a final output of the process. In the following sections we addresses characteristic requirements of each of the steps and asses the feasibility of superellipsoids as volumetric representation for range images and final representation in constructing CAD models for reverse engineering.

2 Range Image Representation

We selected superellipsoids, a subset of superquadrics [1], as parametric volumetric primitives used in range image representation because they can model quite a rich set of shapes with a relatively small number of parameters and because of their apparent correspondence to intuitive notion of parts [11].

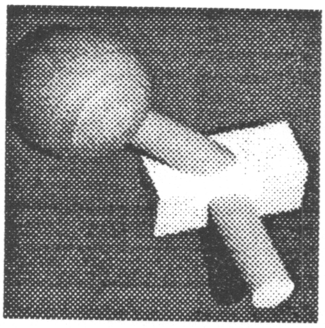
Note that the parts of the surfaces of volumetric models that correspond to no data points are just a

*This research was supported by The Ministry for Science and Technology of The Republic of Slovenia, Project J2-6187.

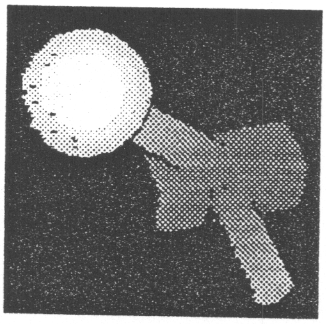
hypothesis. Each superquadric model also encodes the information about the parameter space of ω and η that has been "covered" by the data points. So a complete 3-D description of a part corresponding to a superquadric "covers" the whole parameter space of ω and η. This data could also be used to guide the next viewpoint selection as an alternative to usage of model parameters uncertainty [13].

Recent attempts to formalize the problem of image segmentation as a problem of finding a minimum description length encoding of an image in terms of primitives [7] led to quite general and successful algorithms that can segment the range image in terms of volumetric models directly [8] without previous segmentation in terms of surface models that are latter merged into volumetric models [4]. Informally, the volumetric models produced by segmentation process represent a decomposition of the object into its parts.

To experimentally verify the validity of segmentation algorithm, we used a real range image of a wooden object depicted in Figure 1. The produced list of



a)



b)

Figure 1: a) Intensity image of the object b) Range image of the object

superellipsoids was then used as an input for a range scanner software simulator. The CAD model was rotated about the Y axis for 45° and 135° and corresponding range images were generated. Note that since the model was produced from a single range image, the sphere and the cylinder in Figure 3 are not connected!

Experiments confirmed that recovered parameters of superquadric models from a single viewpoint range image are not a very reliable description of the object parts [14]. But although the recovered parameters are not reliable, we can conclude from the results of experiments that the decomposition of an object into its parts is reliable since it is based on the object structure. Also the model represents the scanned surface with sufficient precision. For example, one of the size parameters of the sphere in Figure 2 is significantly different from the others, meaning that the part as a whole was not reconstructed correctly, nevertheless the surface of the half sphere is modelled with sufficient precision.

Part no.	a_1	a_2	a_3	ϵ_1	ϵ_2
1	50	39	51	1.1	1.0
2	23	27	36	0.1	0.3
3	19	13	50	0.1	1.0

Figure 2: Original CAD model was rotated about the Y axis for 45° and a synthetic range image was produced (left). The segmentation result is presented on the right.

Part no.	a_1	a_2	a_3	ϵ_1	ϵ_2
1	50	39	51	1.1	1.0
2	22	28	60	0.1	0.2
3	15	10	44	0.1	1.0
4	12	16	28	0.2	1.3

Figure 3: Original CAD model was rotated about the Y axis for 135° and a synthetic range image was produced (left). The segmentation result is presented on the right.

3 Range Image Registration

To merge data from different viewpoints into a single coordinate frame, we have to find a rigid transformation between the coordinate frames of range images. We can seldomly rely only on a calibrated sensor setup, so even if we have an estimate of a rigid transformation we should not merge the data blindly but still perform a data driven process of range image registration by using local shape matching. Although the points from the two range images do correspond to the same surface, they do not correspond to the same points on the object surface due to rectangular grid sampling space of the scanner. So we always need some intermediate surface representation of at least one range image for local shape matching leading to range image registration [2,9,3]. To perform a reliable local shape matching we have to determine the subset of points in the first range image and the corresponding region in the surface representations of the second range image that are visible in both range views (see Figure 4). For this we need an estimate of

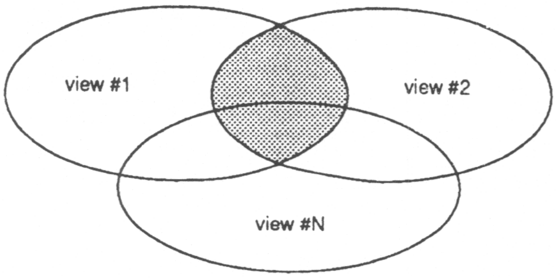


Figure 4: Venn diagram of the object surface points visible from different range views

transformation, which we are about to find. A rough estimate of transformation can be obtained during the object manipulation [3], active sensor repositioning [13] or derived from principal moments alignment. A point in the first range image is used in local shape matching if and only if it passes a spatial neighbourhood test and surface visibility test [12]. The spatial neighbourhood test requires that a point from the first range image must be close to the surface representation of the second image after applying the estimated transformation. While surface visibility test requires that the point in the first range image must be visible from the scanning direction of the second range image. The test is usually simplified by using dot product of surface normal and viewing direction instead of ray tracing. After determining a subset of points from the first range image that is likely to be also seen in the second range image and having initial estimate of transformation we can use one of the iterative registration algorithms [2,9]. Images can be registered without knowing initial estimate of transformation by using regular mesh representation of range images mapped to spherical images [5]. Though the method still achieves the final registration through the iterative registration.

Having a volumetric model representation of the range image, we can easily determine the visible part of the volumetric model in another range view if we know the rigid transformation between views. Since we represented the range image in terms of superellipsoids, we use not only the surface normal criteria but also ray tracing, which is not computationally expensive in case of superellipsoids. The ray tracing approach can give accurate estimates of visibility even for non-convex objects with complex topology. Besides, we might also use the interpolated part of occluded part of the superellipsoids in predicting occlusions.

3.1 Finding Initial Approximation for a Rigid Transformation

The principal moments method is based on the assumption that the object is not symmetrical, that is the directions of principal axis of inertial moments are well defined. From the analytical expressions for the volume of the superellipsoid [6] it is possible to calculate the center of mass of the object. From the expressions for the inertial moments of a superellipsoids [6], we can find a coordinate frame with its origin at the center of mass such that the off diagonal inertial moments vanish. Once we determine such frame for each of the two objects, we are left with four possibilities for the transformation matrix:

- rigid transformation,
- rigid transformation and rotation for 180° about the X axis,
- rigid transformation and rotation for 180° about the Y axis,
- rigid transformation and rotation for 180° about the Z axis,

Simple test based on the part correspondence can determine the right choice for the transformation.

4 Merging range images

After two range images are registered, they have to be merged into a common coordinate frame. The regions of the object that are visible from both range views are represented by two subsets of points forming a redundant and non unique representation. Since the noise properties of the range images taken are mainly dependent on the shape surface normal, we can improve the shape representation in regions commonly visible from different viewpoints by combining several measurements. A simple linear combination of measurements weighted according to the squared cosine of the angle between the surface normal and the scanning direction in proposed in [12]. Ideally, the range image representation should allow incremental update of the representation just in the regions that correspond to range image that is to be added into current representation. Such incremental update was implemented for hierarchical surface representation based on the Delaunay triangulation [12].

Recovering of superellipsoids from range images is formulated as a non-linear least squares problem. Thus it is not possible to incrementally improve the model just by using additional points from the additional range image. Instead we have to perform iterative non-linear least squares minimization using the whole set of points. However we can use the current representation as a starting point for minimization, while the noise properties of the points in common regions can be used in determining the weights of individual points in the objective function.

5 Conclusions

Superellipsoids are good models not only as the final output of the CAD model construction process but also as range image representation at intermediate steps of construction process. The visibility test for a surface point, needed in the of finding the regions in range views visible from booth views, is not computationally expensive. It is based on ray tracing instead of simple surface normal visibility constraint. The same holds for procedure for finding a point on the superellipsoid closest to a given point used in the local shape matching for range image registration.

The authors thank M. Trobina and A. Leonardis for providing the range image and segmentation results, respectively.

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